Journal of Economic Interaction and Coordination (2020) 15:133–158
https://doi.org/10.1007/s11403-019-00275-0

REGULAR ARTICLE

From FDI network topology to macroeconomic instability

Giulia De Masi[1] · Giorgio Ricchiuti[2,3]

Received: 20 November 2018 / Accepted: 27 November 2019 / Published online: 7 December 2019

Abstract

Fragmentation of production undoubtedly constitutes a possible channel of economic contagion and could play a key role in the study of systemic risk. Investments abroad implicitly create long-range economic dependencies between investors and the economies of destination, possibly triggering contagion phenomena. Complex network theory is a primary tool for highlighting economic mutual relationships and paths of contagion, shedding light on intrinsic systemic risks. In this paper, we reconstruct the EU28 foreign direct investments network and study its evolution from 2003 to 2015. Our analysis aims at detecting the changes of topological properties during the crisis, in order to assess how they affected the architecture of economic relationships. Through a detailed study of correlations at different time lags between network measurements and macroeconomic variables, we assess systemic risks. The main findings are: (i) 2009 marks a clear break in network evolution: prior to 2009 the structure was characterized by only one or few hubs/ countries, while in later years a set of connected key nodes emerged; (ii) an increasing heterogeneity is observed in link weights during the entire period analysed (2003–2015); (iii) after 2009, a rewiring of investments is observed towards the EU28 countries that are considered more safe; (iv) time-lagged centrality measures and macroeconomic variables show a clear correlation.

Keywords Foreign direct investment · Economic networks · Network analysis · Systemic risks

JEL Classification F23 · D85

✉ Giorgio Ricchiuti
giorgio.ricchiuti@unifi.it

1 Zayed University, Dubai, UAE

2 Complexity Lab in Economics (CLE), Università Cattolica del Sacro Cuore, Milan, Italy

3 DISEI, Università degli Studi di Firenze, via delle Pandette 9, 50127 Firenze, Italy

1 Introduction

Fragmentation of production is a major feature in modern economies: a process with visible and strong impact on the strategies of firms and countries (both of origin and destination), due to the fact that they have to deal with stronger competition. Firms' capacity to innovate their processes and products, together with their ability to penetrate new markets, are key to their surviving in the new context generated by production fragmentation. Firms respond by developing strategies with an international outlook, as shown by their increased involvement in exports, global outsourcing and foreign direct investments (FDI).

FDIs usually constitute medium-long-term choices for companies. This is even more true when considering greenfield FDI, as in the present study. Furthermore, FDI overlaps with global value chains, intrinsically creating a network between the various countries involved. The choices are therefore not random but involve the development of long-term strategies and their maintenance. Fragmentation of production is also linked to the possibility for firms to diversify risks, related to production activities, between different countries. Choosing a given country as the recipient depends on many factors, both regarding the firm and the country of destination. In particular, for the latter, macroeconomic variables (expected growth, per capita GDP, inflation, etc.) could be considered proxies for the environmental concerns that firms must take into account. Considering these three elements (FDI that constitute an implicit network, firms that diversify fragmenting production and the macroeconomic variables proxy of the medium-long-term reliability of a country), we believe it is worth analysing how the topology of the FDI network and its evolution may correlate with macroeconomic variables, providing indications on systemic risk. Furthermore, this will enable us to better identify the trade-off between systemic and sharing risk.

According to Schwarcz (2008), the common element between the various definitions of systemic risk is the domino effect . There is an initial cause that produces a series of negative economic effects. For this reason, in this paper, systemic risk refers to a situation in which instability in one country leads to instability in another one (see for example, Recchioni and Tedeschi 2017). FDIs naturally create a network of reciprocal externalities (positive or negative) between a pair of countries; links between countries could be a possible source of economic contagion. When studying the 2003–2015 period, we investigate changes in network structure (focusing specifically on node centrality indexes) during the crisis of 2009. In particular, keeping in mind the possible spread of risks, we ponder whether FDI flows affect the economic performance of European countries. Given the intrinsic FDI network structure, we do not correlate FDI directly with macroeconomic variables but with FDI network indexes. Moreover, we do an exploratory analysis to understand whether network topology measures anticipate (or follow) macroeconomic changes.

Systemic risk is an issue linked to two kinds of phenomena widely studied in complex networks: propagation of failures/damages and epidemic spreading. It has been shown that uncorrelated scale-free (SF) networks show an exceptional tolerance to random damages (Zhao et al. 2004), while they are highly vulnerable to intentional attacks. On the other hand, SF networks are also the ideal media for the propagation of infections, bugs, or unsolicited information (Pastor-Satorras and Vespignani

2001), while for homogeneous networks, it is possible to distinguish between a healthy/inactive phase where the virus cannot propagate or can be easily confined, and an endemic/active phase where the virus propagates through the network. According to the above, the particular dynamics of both propagation of failures/damages and epidemic spreading in a SF network are due to the hierarchical dynamics typical of spreading on scale free networks: once the highly connected hubs are reached, both infection and damage pervade the network in a progressive cascade across smaller degree classes. These ideas encouraged economists to analyse how changes in the network structure can explain the chain failures of the system, for example in credit-debit or in the interbank network (i.e., Berardi and Tedeschi 2017; Lenzu and Tedeschi 2012), in the customer–supplier relationship (Arata et al. 2018) as well as other financial networks (Hautsch et al. 2015; Acemoglu et al. 2015).

These models are very well established in the network field. However, in recent literature, some authors have linked topology measures and systemic risks. For example, Battiston et al. (2012) propose a debt rank methodology, based on eigenvector centrality, applied to FED loan programs to financial institutions. Kuzubas et al. (2014) emphasize the connection of centrality measurements and systemic risk in the interbank market during the Turkish crisis of 2000. Very recently, looking at the credit market, Asgharian et al. (2019) found a correlation between centrality measurements and $\Delta CoVar$. In this paper, we follow the second approach, based on the relation between centrality measurements (of the FDI network)and macroeconomic variables in order to reveal a systemic risk.

To begin with, we analyse the evolution of the EU28 FDI network in the 2003–2015 period, so as to understand whether a structural change occurred in the network during the crisis. We subsequently study the cross-correlations between macroeconomic variables and network indexes with the intention to identify signals of systemic risk. However, it is worth noting that FDI are different from debt–credit relationships. If a more connected network could lead us to imagine a systemic risk that spreads faster, it could also be the result of a greater diversification of investments in order to limit the damage caused by a crisis, with a consequent reduction in systemic risk.

Network analysis is mainly used, in empirical literature, to study the structure of the bank-firm credit market (De Masi et al. 2011; Battiston et al. 2007), the interbank market (Iori et al. 2008; De Masi 2008), financial market investments (Garlaschelli et al. 2005), world trade (Fagiolo et al. 2009; De Benedictis and Tajoli 2011). As regards the fragmentation of production, Criscuolo and Timmis (2017) map the global value chains, detecting the main hubs in terms of countries and sectors with a core-periphery approach.

The application of network analysis to FDI has recently been growing. Wall and van der Knapp (2011) analyse—in more than 2000 cities worldwide—the network of the top 100 global multinational and ownership linkages, making a distinction between the producer service sector and all industrial sectors. More recently, Alfaro and Chen (2014) use measurements of network density to study agglomeration phenomena in order to analyse a worldwide database of multinationals. Garas et al. (2016) analyse the relation between the network of migrants and that of FDI, while

Metulini et al. (2017) study how the FDI network affects the trade network. Rungi et al. (2017) study the links between ownership and firms' control all over the world.

Moving to European countries, network-based analyses on Italian foreign investment data (De Masi et al. 2013) and on French data (Joyez 2017, 2019) have been performed. In a recent work, De Masi and Ricchiuti (2018) reconstruct the network of European (EU28) firms co-investing in the same countries, by studying—separately—the years 2003 and 2015. Starting with a bipartite network model with two kinds of nodes (countries and investors), and studying the projections in investor space, they highlight the occurrence of heterogeneity in investment strategies between and within sectors, stressing the emergence of common strategies among firms. They detect the presence of subnets and main hubs (in terms of firms) also within specific sectors, and, by qualitatively analysing the main actors, they discuss the choice to develop new projects.

Since the primary aim of this paper is to study the role of networks in systemic risk, as well as mutual dependencies among countries as a result of FDIs, we use a different definition of nodes and links.[1] In particular, the network is defined as follows: two countries are linked if a firm belonging to the first is investing in the second. This representation is particularly suitable for a study of systemic risk related to FDI. We study the evolution of the EU28 country network which emerged during the entire period (2003–2015). We take data from ‘fDi markets’: a very rich, global, detailed database developed by the Financial Times, which contains information on worldwide greenfield FDI. 38 networks have been analysed, one for each industrial sector. Through a detailed study of correlations at different time lags between network measurements—particularly centrality measurements—and macroeconomic variables, we assess systemic risks. The main results are: (i) 2009 marks a clear break in network evolution: prior to 2009 the structure was characterized by only one or few hubs/ countries, while in later years a set of connected key nodes emerged; (ii) an increasing heterogeneity is observed in link weights during the entire period analysed (2003–2015); (iii) after 2009, a rewiring of investments is observed towards the EU28 countries that are considered more safe; (iv) time-lagged centrality measures and macroeconomic variables show a clear correlation.

After a brief presentation of the data (Sect. 2), in Sect. 2.1, we present the methodology employed to build the network and the topology measures used, and discuss the evolution of the network (in Sect. 3). We present heat-maps on the correlations between topology measures and economic variables (Sect. 4): although correlation results are exploratory, they still show direction of causality. Final remarks conclude the paper.

2 Data and methodology

fDi markets are one of the main global databases providing FDI information. Since 2003, it has been monitoring real-time investments made by companies worldwide. It now contains data on more than 80,000 firms. It records only greenfield FDI, it gives information (country of origin and destination, an estimation of capital investments, possible job creation) about firms’ projects (the name used in fDi markets instead

[1] The network definition is different from De Masi and Ricchiuti (2018), where the authors used the same dataset. In that paper, a bipartite graph was first defined, then projected on investors’ and countries’ spaces. This methodology was useful for detecting common strategies among countries and investors.

of affiliates) for investing abroad. Information is taken up by the media, industry organizations, investment agencies, and official corporate publications.

In this study, we focus on EU28 outward greenfield FDI in the period from 2003 to 2015. We do not use information regarding capital investments and the number of workers because it is too not complete and with too many missing values. Using flow data, we can better analyse how firms' choices evolve and how they impact both countries of origin and destination. Finally, we use the World Development Indicator of the World Bank to get information on Domestic Credit (%GDP), Current Account (%GDP), GDP growth, GDP per capita growth, Inflation (as % change of the GDP deflater), Trade (Import plus Export as %GDP), FDI net flows (as %GDP). Finally, from Bloomberg we obtained the 10 years Yield of public bonds in the different EU28 countries.

2.1 Methodology

The FDI dataset allows us to define a FDI network. Nodes are countries ($C = C_1, C_2, \ldots, C_{N_C}$), in particular EU28 countries in the current study. A link between two nodes C_i and C_j is drawn if a company based in country C_i is making an investment (i.e., opening an affiliate) in country C_j. An adjacency matrix A is defined, having elements $a_{ij} = 1$ if C_i and C_j are connected, $a_{ij} = 0$ otherwise. A weight is associated to the links: it represents the number of investments from C_i to C_j countries. The weighted adjacency matrix W is defined, where the generic element w_{ij} represents the weight of the link between C_i and C_j. Since FDI flow data are analysed here, a completely new network is generated for each year. Flow data appear to be more suitable than stock data for the study of the relation between FDI and systemic risk, due to the effects on the balance of payments, the (real) exchange rate (i.e., the Dutch disease) and on GDP growth.

The original network is both weighted and directed. FDIs build a mutual relationship between two countries where a static direction is easily defined (from the investing country to that of destination). However, dynamically, the role of direction is ambiguous. While in debt networks, a path of contagion has a clear direction, it is not the same for FDI networks. Indeed, a country slowdown can both reinforce another country as well as make it weaker. In fact, firms can either decide to invest abroad in order to respond to the deterioration of economic conditions, or not to do so, thus avoiding a greater exposure to economic risk. For this reason, after some basic statistics on the directed network, we decided to make the matrix symmetric as is usually done for similar networks, such as trade networks.

More specifically, starting from the above described dataset, a network is defined for each year and for each industrial sector. Given that 13 years of data and 38 sectors are available, this leads to the generation of a total of 494 networks. A set of local-scale, meso-scale and large-scale network topological measurements are considered:

(A) Local:

- at first order: degree and strength;
- at second order: average neighbor degree;

- at third order: clustering;
- at fourth order: squared clustering.

(B) Higher order measurements:

- betweenness;
- closeness;
- eigenvector centrality;
- eccentricity.

These centrality measurements are considering binary networks, neglecting weights of links.

Many definitions of 'centrality' have been proposed in network analysis. We consider four of them. A first measure of centrality of a node is the **degree centrality**, achieved dividing the degree by the number of nodes of the network:

$$dc_i = k_i/(N-1); \tag{1}$$

where N is the total number of nodes.

A second definition, the **betweenness centrality** (Brandes 2001), is based on dynamical properties of the graph and is given by the number of times that one vertex k is crossed by minimal path from one vertex i to j. Let's define d_{ij}, the distance between two vertices i, j, as *the shortest* number of edges to go from i to j, that is:

$$d_{ij} = \min_{\forall \mathcal{P}_{ij}} \left\{ \sum_{k,l \in \mathcal{P}_{ij}} a_{kl} \right\} \tag{2}$$

where $\mathcal{P}_{ij}$ is a path connecting vertex i and vertex j. Therefore, the betweenness centrality b_i is defined :

$$b_i = \sum_{\substack{j,l=1,N \\ i \neq j \neq l}} \frac{d_{jl}(i)}{d_{jl}} \tag{3}$$

where d_{jl} is the total number of different shortest paths (distances) going from j to l and $d_{jl}(i)$ is the subset of those distances passing through i. The sum runs over all pairs with $i \neq j \neq l$.

Another measure of centrality employed is the **closeness centrality** (see Freeman 1977 and Sabidussi 1966):

$$cl_i = \frac{N-1}{\sum_j d_{ij}} = \frac{1}{\bar{d}_i} \tag{4}$$

which is the reciprocal of the average distance of one node from the other nodes. In order to be a hub, a country should not be very distant from all the others.

The last measure of centrality employed is the **eigenvector centrality** Newman (2010) which measures the importance of a node based on the score of its neighbours. Contrary to the previous measures, this one is not based on distance among nodes, but depends recursively on

the centrality of the neighbours. In vector notation, the eigenvector centrality c is the vector that solves the equation $W \cdot c = \lambda c$ where λ is the largest eigenvalue. In terms of recursive expression, we can define the eigenvector centrality of node i as

$$c_i = \frac{1}{\lambda} \sum_j W_{ij} c_j \tag{5}$$

It is intrinsically based on the spectral properties of adjacency matrix. So it provides a different approach to assess node centrality.

Finally the **eccentricity** of a node is

$$e_i = \frac{1}{\max_{\forall j \in N} d_{ij}} \tag{6}$$

that is the inverse of the maximum distance of that node from any other possible node of the network.

As pointed out by Krackhardt (1990) different centrality measures identify distinct nodes as hubs, even if a certain correlation among the above dimensions is observed. Within each sector, the evolution of the above measurements is analysed year by year, both at aggregated level (the mean values on all the nodes) and node by node. The centrality measurements (particularly closeness, betweenness and eigenvector centrality), typical of meso-scale level network analysis, cannot be reduced to traditional statistical measurements. At this level, network analysis is showing its most explanatory power, giving an added value compared to traditional techniques.

At large-cale level, we have investigated the density $\rho = 2L/[N(N-1)]$, where N is the order of the graph (defined as the total number of nodes) and the size L (defined as the total number of links): therefore density is the ratio between the number of observed links and the number of possible links. The contribution of network analysis to the study of systemic risk is at the mesoscopic scale, shedding light on the architecture of mutual dependencies between countries, where traditional statistics cannot arrive. In particular, while global scale measurements and local first order measurements can be reduced to equivalent econometric dimensions, centrality measurements do not have an equivalent in traditional statistics, because they consider the mesoscopic structure of mutual relationships.

Finally, a null hypothesis model has been implemented for each specific network. Starting from the initial investments of each country, destinations have been randomized. This preserves the intention of each specific country to make an investment and only the destination is changed. Another approach to the null hypothesis model has also been adopted: starting from the initial investment project list, both origin and destination have been randomized. However, the first procedure is more strict: if a network looses internal architecture with the first reshuffling procedure, the observed network is random. For this reason, we report only the results from the first null hypothesis methodology.

3 The evolution of the FDI network

3.1 Network evolution for all sectors

In Fig. 1(left panel), we report, year by year, the number of projects in the whole sample (black line) and in EU countries (Grey line). Considering all 38 sectors within the entire database, there were about 1600 and 3000 EU28 investors in 2003 and 2015, respectively, corresponding to almost 3100 and 5200 projects. On average, an EU28 investor had 1.9 projects in 2003 and 1.7 in 2015, but with large heterogeneity across sectors. The number of EU-based investors is shown by the red line. There is an initial upward trend until 2008 and, following a small decrease, the number stabilizes around 6000 projects per year. The pattern is similar, though much smoother for projects within EU28 countries: after an increase in the first part of the last decade, there was a reduction suddenly after the crisis. Moreover, in recent years, the number of projects has been stable at around 2000. Therefore, almost half of the EU28 projects are directed within the Union itself.

More relevantly, from the point of view of network structure, the density is fairly constant despite the trend observed in investments. As clearly visible in Fig. 1(right panel), the density of EU28 FDIs is between 0.53 and 0.6. Figure 2 shows that the

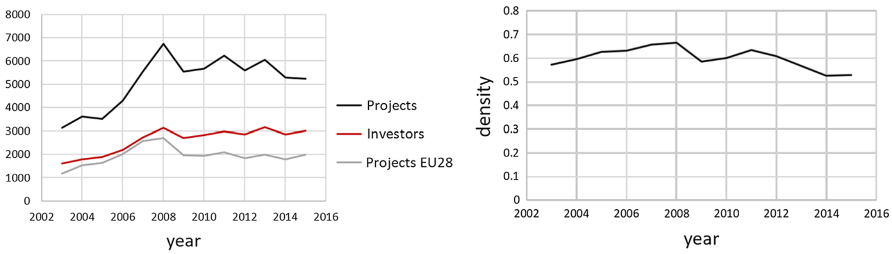


Fig. 1 Evolution of number of investors (red line) in the whole sample and number of projects worldwide (black line) and inside EU countries (grey line) during the 2003–2015 period (left panel). Evolution of density of country network during the 2003–2015 period (right panel) (colour figure online)

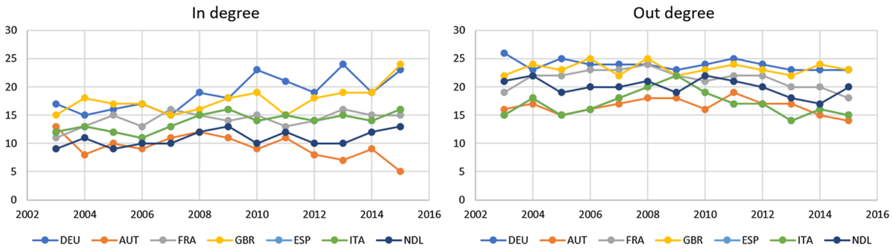


Fig. 2 Evolution of in-degree (left panel) and out-degree (right panel) for the EU countries most active in FDI

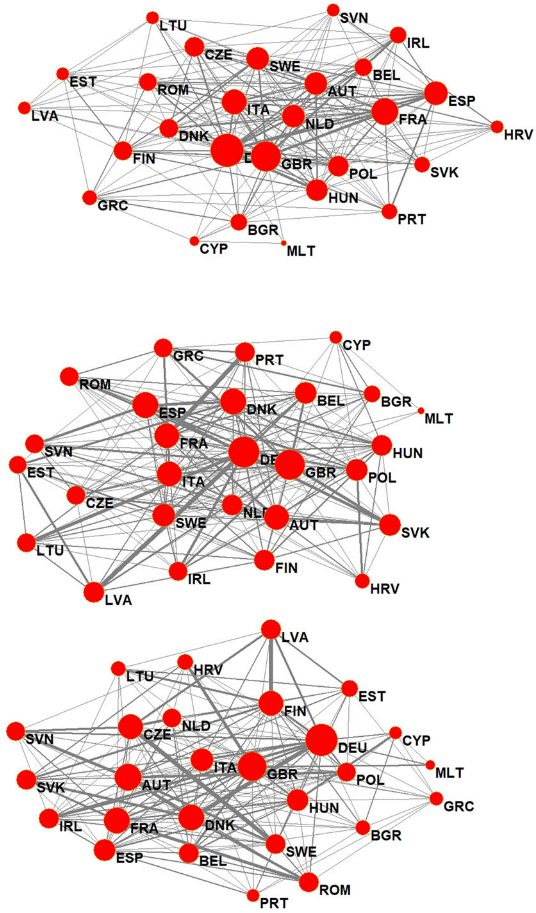


Fig. 3 Graphs of EU28 FDI network for 2003 (top panel), 2009 (middle panel) and 2015 (bottom panel). While the number of nodes is constant, a big change of links can be observed

in-degree and out-degree of the EU countries most active in FDI are pretty constant. Strong economies (like Germany and the UK) show an increase of incoming degree after the crisis because they are attracting FDI, while other countries, like Austria, are less attractive. This can be explained by the fact that the number of links among countries is almost constant. However, a rewiring of links is observed (with a change in origin and destination countries), together with a relevant change in the values of weights (number of investments) during the 2003–2015 period. This is evident from a qualitative point of view from the three graphs in Fig. 3.

The graph depicts the EU28 FDI country networks in all the sectors for years 2003, 2009 and 2015. The procedure employed to visualize the graphs is the Kamada-Kawai algorithm (Kamada and Kawai 1989; Pajek 5.03, http://vlado.fmf.uni-lj.si/pub/networks/pajek/): it is based on the idea that the geometric length between two country-nodes shows the topological distance between them in the graph. Therefore, countries that are closer in the graph are more strongly connected. The size of the nodes represents the weighted degree centrality, while the thickness of the link shows the

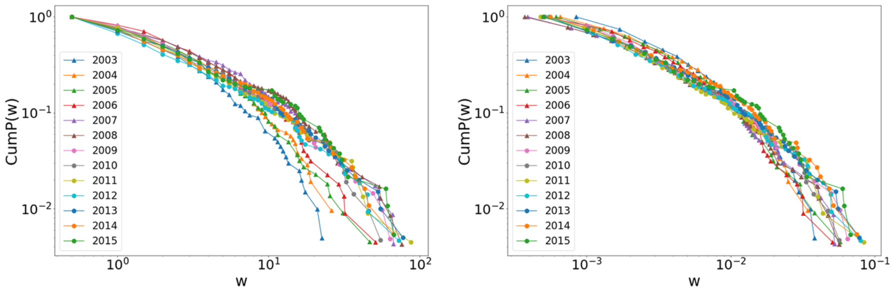


Fig. 4 Evolution of cumulative distribution of weights (left) and normalized weights (right) on loglog scale during the period 2003–2015

weight of the link.[2] While the number of nodes is constant, a big change of links can be observed. Some channels of FDI become relatively more important than others: in the first network links are quite homogeneous, while moving forward along the 2003–2015 period, the heterogeneity within the same network of both node sizes and links keeps increasing.

Quantitatively, the change in weights is evident from Fig. 4(left panel).[3] Weight distribution is moving to higher values of w, with an even stronger emergence of heterogeneity. This trend is independent from a slight increase in the total number of investments during the first years, as shown in Fig. 4 (right panel), that shows a very similar behaviour, where the normalized weights are reported, that is—for each year—$\frac{w_{ij}}{\sum_{ij} w_{ij}}$. Heterogeneity increased very fast during the 2003–2009 period, while after 2009, there appears to be a slowing down of the to higher values. Curves start to become closer showing that heterogeneity has stopped growing. This could be due to a smaller tendency to invest only in certain preferred countries. Looking at the graph, Germany, France, Great Britain and the Netherlands become progressively the key players of FDI, as already observed in Fig. 2.

In order to shed light on the change of the network's structure, in Fig. 5 we show four centrality measurements from 2003 to 2015, namely degree, betweenness, closeness and eigenvector centrality distributions. The cumulative degree distribution shows that curves are moving towards higher values of k, so to large heterogeneity of countries' degree. In 2009, a strong bending of the distribution curve to a lower value is observed. There is no a dominant hub anymore, but many main actors are more connected.

The betweenness distribution starts from heavy tails in 2003, bending abruptly in 2009 towards a lower values tail and then relaxing again to heavy tails after 2009. A similar trend is observed for closeness centrality and betweenness: around 2009, the

[2] Only for visualization reasons, given the heterogeneity of the values, we chose to use as size of nodes and links, the square root of degree centrality and of real weight respectively; in this way the variability of values, that would make the graph not clearly readable, is reduced.

[3] Figure 4 shows both the cumulative distribution of unnormalized and normalized weights. Heterogeneity is fully evident from the unnormalized weights' distribution. At the same time, the small effect of a certain increase of the total number of investments during the first years until 2008 has been removed in the normalized weights' distribution. Our focus is on the change of the slope of the distributions which is preserved in both graphs, given that the plots are on a double logarithm scale. The results confirm what emerges from graph visualization.

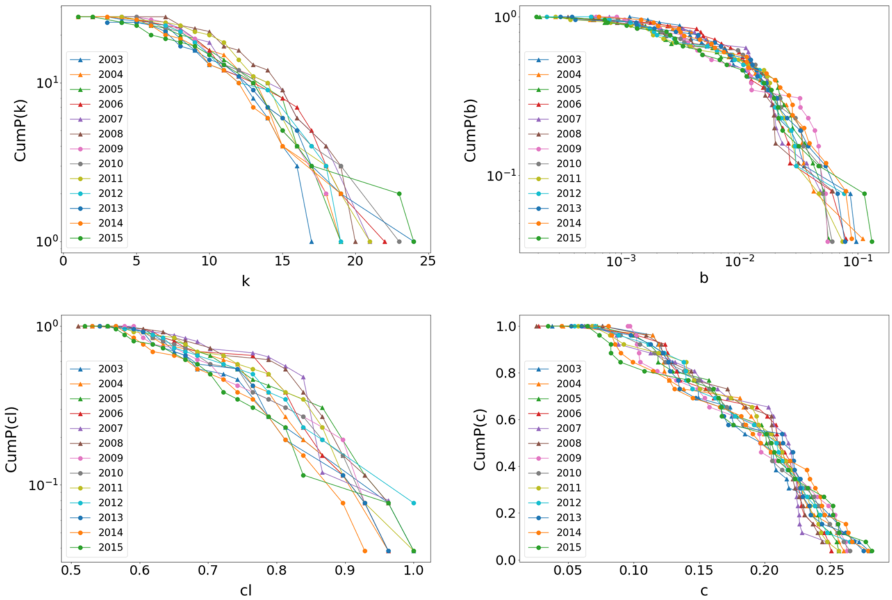


Fig. 5 Evolution of cumulative distribution of degree (top left panel), betweenness (top right panel), closeness (bottom left panel) and eigenvector centrality (bottom right panel) during the 2003–2015 period

distribution is the steepest, with a lowest maximum value of centrality, like a cut-off value. This shows that the network is more connected while the distance between each pair of nodes has decreased. This change in the number of links could be explained as follows: in 2009, as a reaction to the crisis, firms tried to reduce heterogeneity, in particular by avoiding to have very few nodes with high centrality (hubs) due to the activation of alternative channels of investments. The year after, the system switched to a structure which privileged a higher number of central investment countries. Eigenvector centrality, on the contrary, shows the 2009 curve (in the high values region) is the most external, meaning that in 2009 the highest eigenvalue centrality value is observed as well as the highest number of nodes with high eigenvalue centrality. This is a further evidence of the emergence of a set of main actors.

This could be explained by the higher presence of several nodes with similar degree, without a main role attributed to one or a small number nodes. The same conclusion can be reached with respect to closeness distribution where, in 2009, the lowest maximum value of closeness was observed, with several nodes populating the right part of the distribution. To sum up, while before 2009 there were few key countries in the FDI network, after the crisis many nodes emerged but with a lower value of centrality. Therefore, there was a change in the network structure. At the same time, as regards weights, heterogeneity continued to grow throughout the entire period but at a lower rate.

3.2 Sectorial networks

While the above evidence emerged from the network's sectors as a whole, some differences between sectors were nonetheless noted. We selected a traditional sector (Industrial machinery) and a new sector (IT), which are characterized by a higher number of projects. In Figs. 6 and 7, the network of Industrial machinery and IT sectors are shown for years 2003, 2009 and 2015.

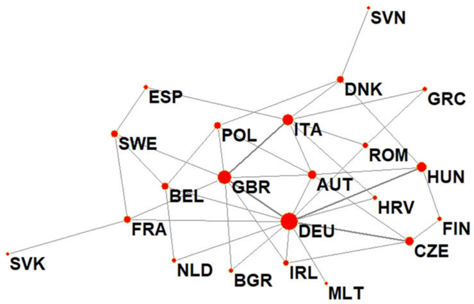
Figure 8 shows the different ways the two sectors adapted to the crisis. In the traditional sector (Industrial machinery), the maximum heterogeneity is observed in 2009, in progressive growth. After 2009, a strong trend reversal is observed towards lower values of weights. On the contrary, for the emerging sector (IT), the heterogeneity keeps increasing also after 2009, moving the distribution towards higher values of tails. This is also evident from Fig. 7 where the size of nodes is proportional to the strength of countries. The same result emerges also from the analysis of the underlying network structure, particularly from the betweenness distribution. The topology of Industrial Machinery network initially evolves towards a configuration with few very central nodes. After the crisis, starting in 2009, the topology moves back to a more connected structure with a set of nodes sharing similar centrality because of their mutual links. In the case of the IT sector, on the contrary, there is a continuous trend from a topology with few central nodes towards a more connected net with a set of countries sharing high centrality. So we can conclude that the IT sector is less affected by the crisis. The trend is clear and without any structural break.

Finally, in order to compare the topological quantities of empirical and randomized networks, a randomization procedure has been used. The null hypothesis model randomizes the network, preserving the firms of the country of origin and changing only the destination country. The adopted procedure is very strict. In Fig. 9, a null hypothesis graph for the IT sector is shown. It is evident that heterogeneity has been removed by randomization: the graph approaches a random graph. This result is confirmed for all sectors.[4] It should be noted that the nodes have a more homogeneous size between them, and this is due to the fact that FDI are randomly distributed on the possible links. Consequently, this is strong proof the presence of main privileged channels in the true network: the FDI network is not random.

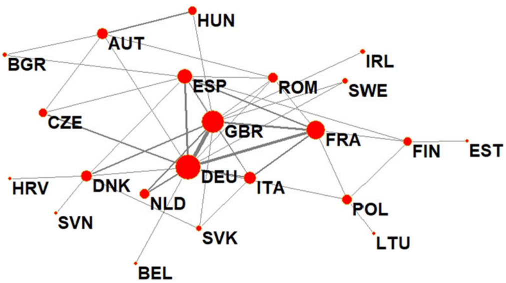
Table 1 shows a year-by-year comparison of the topological measures investigated in the paper, in particular between the original IT networks and the corresponding null hypothesis networks. It is clear that the randomized network, which is not based on a particular strategy other than the initial intention of every firm to make a certain number of investments, is much more connected. As a consequence, the k-core[5] size is much higher; the same is true for degree, clustering and degree centrality, as expected. The average betweenness of the randomized network is lower than in the observed network. Also, closeness centrality is higher, because of the higher availability of paths between any pair of nodes. For the same reason, eccentricity is lower. The eigenvalue centrality seems less affected by randomization. This demonstrates that, in real networks, firms have preferred countries of investment and apply a strategy

[4] The other graphs are available upon request.

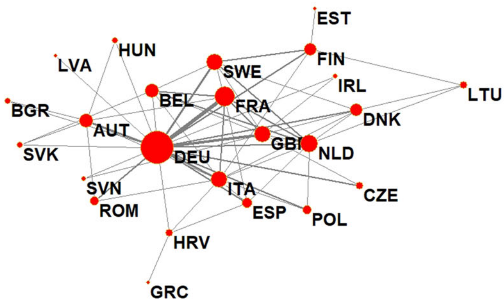
[5] A k-core is a maximal subgraph that contains nodes of degree k or more.



2003



2009



2015

Fig. 6 Industrial machinery network. The size of nodes is proportional to degree centrality. The thickness of links represents the number of investments between the two countries

which is far from being random. Also, the distribution of weights is very different when comparing the real network and the null hypothesis model, as shown in Fig. 10. Years 2003, 2006 and 2015 are shown here.[6] Dotted lines represent the distribution of real normalized weights, while the lines with triangles represent the corresponding

[6] All the distributions of the other years and sectors can be provided.

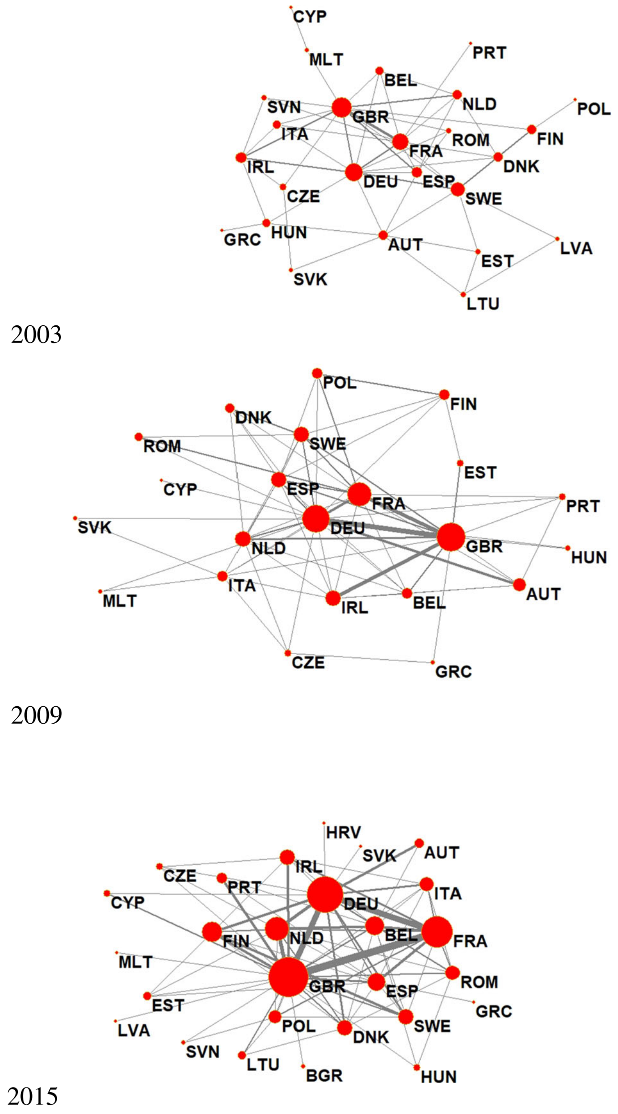


Fig. 7 Software and IT network. The size of nodes is proportional to degree centrality. The thickness of links represents the number of investments between the two countries

random networks. For each year, it is evident that the distribution of real weights has fat-tailed characteristics, as opposed to the null hypothesis networks. The role of link heterogeneity clearly emerges, showing a significant difference between real investment and random investment networks.

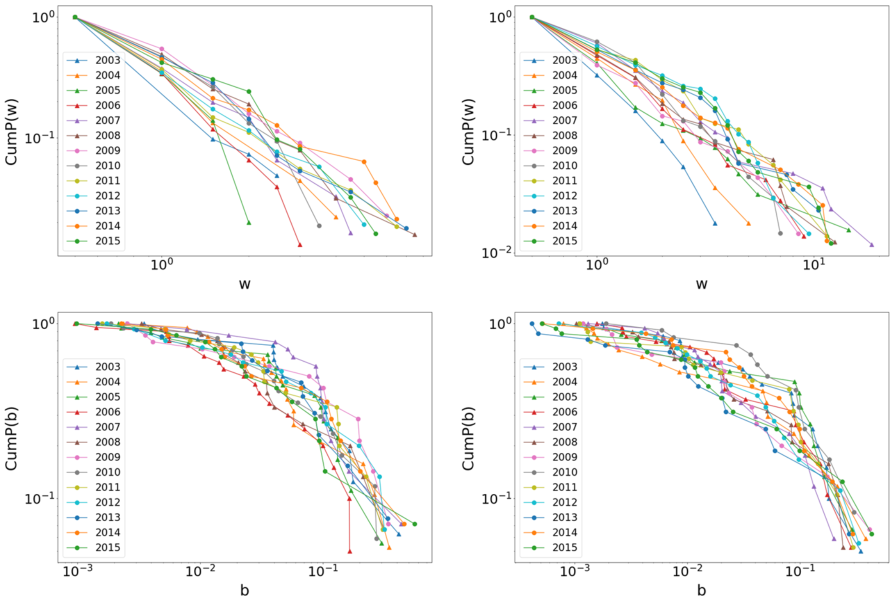


Fig. 8 Evolution of cumulative distribution of weight (top) and betweenness (bottom), for two sectors: industrial machinery (left) and IT (right) during the 2003–2015 period

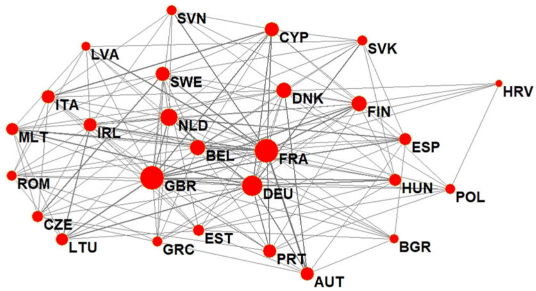


Fig. 9 Null hypothesis graph for software and IT network (2015). The size of nodes is proportional to degree centrality, while the thickness of links represents the number of investments between the two countries. As we can see, the heterogeneity is removed by reshuffling and the graph approaches a random graph

4 Aggregated indexes and heat-maps

The networks have been built sector by sector. Therefore, in order to analyse the most central destination countries, we aggregate the topological measures as follows:

$$\text{Index}_{it} X = \frac{1}{N} \sum \lambda_{ijt} \text{Index}_{ijt} \tag{7}$$

where X is one of the indexes described above, N is the number of sector and λ_{ijt} is, for each country i, the ratio between number of projects in sector j over the total number of projects in the year t. While Index_{ijt} is the Index of sector j of country i in the year t.

In Table 2, the main descriptive statistics of the calculated indexes are shown for all the years considered. Values are very small because the index takes all sectors

Table 1 Most relevant topological properties showing the comparison between real IT network evolution compared to the evolution of the corresponding randomized network

Year	k core size		Average degree		Average clustering		Average degr centrality	
	Original	Reshuffled	Original	Reshuffled	Original	Reshuffled	Original	Reshuffled
2003	8	15	4.48	5.26	0.36	0.23	0.18	0.19
2004	9	10	5.09	6.37	0.35	0.52	0.23	0.24
2005	9	14	5.57	7.41	0.54	0.56	0.24	0.27
2006	9	13	6.00	8.00	0.48	0.62	0.25	0.30
2007	12	21	8.10	10.89	0.64	0.63	0.39	0.40
2008	8	14	6.48	9.78	0.49	0.62	0.26	0.36
2009	7	19	6.27	8.30	0.63	0.50	0.29	0.31
2010	11	13	6.18	9.04	0.61	0.57	0.28	0.33
2011	11	15	5.54	10.15	0.45	0.72	0.21	0.38
2012	14	19	6.00	10.30	0.49	0.64	0.26	0.38
2013	11	21	6.69	11.78	0.62	0.62	0.26	0.44
2014	8	21	6.32	11.19	0.52	0.61	0.25	0.41
2015	12	25	6.15	11.85	0.55	0.59	0.23	0.44

Table 1 continued

Year	Average betweenness		Average closeness		Average eigenvalue centr.		Average eccentricity	
	Original	Reshuffled	Original	Reshuffled	Original	Reshuffled	Original	Reshuffled
2003	0.06	0.04	0.45	0.49	0.16	0.17	3.76	3.19
2004	0.05	0.03	0.54	0.56	0.18	0.17	2.73	2.59
2005	0.05	0.03	0.53	0.58	0.18	0.17	3.13	2.52
2006	0.04	0.03	0.53	0.60	0.17	0.17	3.58	2.26
2007	0.03	0.02	0.63	0.65	0.20	0.18	2.52	2.00
2008	0.04	0.02	0.54	0.63	0.17	0.18	3.20	2.00
2009	0.04	0.03	0.58	0.59	0.18	0.18	2.45	2.56
2010	0.04	0.03	0.56	0.61	0.18	0.18	2.86	2.07
2011	0.05	0.02	0.50	0.64	0.16	0.18	3.65	2.00
2012	0.04	0.02	0.54	0.63	0.18	0.18	3.00	2.15
2013	0.03	0.02	0.51	0.66	0.22	0.18	2.23	2.00
2014	0.04	0.02	0.54	0.65	0.17	0.18	2.72	2.00
2015	0.03	0.02	0.55	0.66	0.16	0.18	2.67	2.07

Fig. 10 Comparison of cumulative distribution of normalized weights of the IT network for the 3 selected years: 2003, 2009 and 2015. The circles represent weights from real networks, triangles from the randomized network

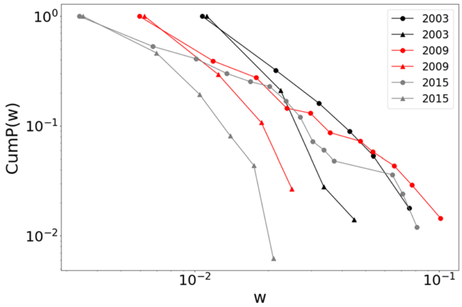


Table 2 Summary statistics

Variable	Mean	SD	Min	Max
Index-degree	0.107	0.07	0.026	0.348
Index-av. neighbour degree	0.196	0.055	0.063	0.507
Index-clustering	0.009	0.005	0	0.025
Index-clustering 2	0.006	0.003	0	0.025
Index-betweenness	0.001	0.002	0	0.011
Index-closeness	0.012	0.002	0.003	0.018
Index-eingenvector centrality	0.005	0.003	0.001	0.016
Index-eccentricity	0.091	0.012	0.037	0.143

Table 3 Highest index degree for EU countries

2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015
DEU	GBR	GBR	DEU	GBR	GBR	GBR	GBR	DEU	DEU	DEU	DEU	GBR
GBR	DEU	DEU	FRA	DEU	DEU	DEU	DEU	GBR	GBR	GBR	GBR	DEU
ITA	NLD	SWE	GBR	FRA	FRA	FRA	FRA	ESP	ESP	NLD	FRA	NLD
FRA	FRA	FRA	SWE	POL	NLD	NLD	ESP	FRA	FRA	FRA	ITA	FRA
AUT	AUT	AUT	AUT	AUT	AUT	ESP	AUT	ITA	NLD	ESP	SWE	BEL

into consideration. Moreover, there is not much dispersion in distributions, because investments in all sectors do not take place in all countries. In Table 3, we indicate, year by year, the hubs (countries) of the networks emerged using the Index of degree. It is worth noting that, countries with the highest degree are also the most important (in terms of population and GDP) EU countries: UK, Germany, France. They are followed by Italy, Austria, the Netherlands, Spain and Sweden. As already seen in Fig. 2, these countries are both an origin and a destination of investments.

It is worth stressing that, while the outgoing links appear to have remained stable during the 2003–2015 period, the number of incoming has shown an increase after the crisis, particularly for Germany and Great Britain, which means that they are attracting more investments.

Finally, Figs. 11 and 12 show maps for the years 2003,2009 and 2015 of the sum of projects per country and the eigenvector centrality Index, respectively. The countries are divided into quartiles. Visually, the projects are concentrated—in the period considered—in the central EU countries (Germany above all), but they move from the more peripheral countries (in 2009) to the EU founding countries(in 2015). On the other hand, looking at the eigenvector centrality index, it is clear that the map has concentric circles. The core consists of the EU founding countries plus Spain and the UK. A second and third circle are also highlighted as you move away from the centre.

To sum up, even though we are analysing FDI flows, the network structure is very compact and its leaders do not change from year to year. However, the distribution of both links and weights shows significant changes around 2009. The crisis has stopped the evolution of the network, changing corporate strategies and, consequently, the network topology (i.e., the hubs). These seem to be concentrated in a small number of countries so as to diversify the risk. Our idea is that a more compact FDI network could transmit the weaknesses/strengths of the economic system from one country to another, increasing/reducing the systemic risk. Indeed, it is difficult to understand whether network evolution has (or has not) favoured contagion or, instead, has been a stabilizing element for the countries (both of origin and destination) themselves. It is clear that there is a trade-off between systemic risk and risk sharing. For this reason, in the next section, we analyse if there exists, and in which direction, a correlation between network evolution (proxied by its indexes) and macroeconomic variables. In this case, network topology indexes could be used as early warning systems of a crisis. FDI networks can help us understand how weaknesses/strengths are transmitted between the various economic systems (countries). Therefore, we run correlations (using also lags) of the network indexes to some macroeconomic variables, in order to understand their sign and magnitude.

Figures 13, 14 and 15 contain heat-maps of correlations between our indexes and macroeconomic variables for EU countries.[7] The least correlated indexes with the chosen macroeconomic variables are clustering and squared clustering. On the other hand, the betweenness and eigenvector centralities present the maximum values for correlations. Looking at the macro variables, the strongest are between our indexes and trade variables (import, export and trade). This is true in both directions: they are (negatively) correlated with the current values of the indexes, and its delays. Most probably, European investors—observing that the crisis had already started in the US—changed their strategies towards a more conservative approach. This change of topology is producing an effect on macroeconomic variables. Moreover, this result could indicate that there may be substitutability between imports/exports and FDI. Countries that are key network players register a reduction of both imports and exports (as % of GDP), perhaps because firms prefer to move there to produce. On the other hand, a change in macroeconomic variables produces a change in investment strategies, which leads to a change in network topology. We believe that this negative correlation is (mostly) driven by the increasing centralization of the network around big European countries (in terms of GDP, i.e., Germany, France and Great Britain). We therefore rescale trade variables, attributing to all countries a value of 100 for year 2003. By

[7] All correlations are significant at 5%.

doing so, correlations with many Indexes—changing sign—have a (significant) but *positive* relationship with trade variables and those correlations, whose signs remain negative, present a lower magnitude. In our view, this is a clear confirmation that the negative correlation should be a between and not within country effect.

It also emerges that centrality measures are positively correlated to the current account balance, indicating that being a leader of the FDI network brings benefits to the current account: countries are indeed linked along the global value chain (see Criscuolo and Timmis 2017). On the other hand, topology measures are negatively correlated to Yield10, showing, in our opinion, that countries with high debt present a greater (country) risk to firms. Furthermore, the latter prefer to invest elsewhere. Finally, GDP growth and GDP per capita growth, inflation and deficit are weakly or not at all correlated.

Two considerations are important. First, we made the correlations on the whole sample, assuming that there are no significant country fixed effects. However, taking into account single countries, some correlations show stronger magnitude.[8] Moreover, our indexes should be considered as the weighted averages of the indexes of the various sectors. Correlating the values of the individual sectors could give us different indications.

To sum up, the most interesting results are the following:

- centrality measurements, i.e., degree, closeness, betweenness and eigen-centrality, have a similar pattern;
- they are negatively correlated to export, import, trade and yield, while they are positively correlated to the current account.

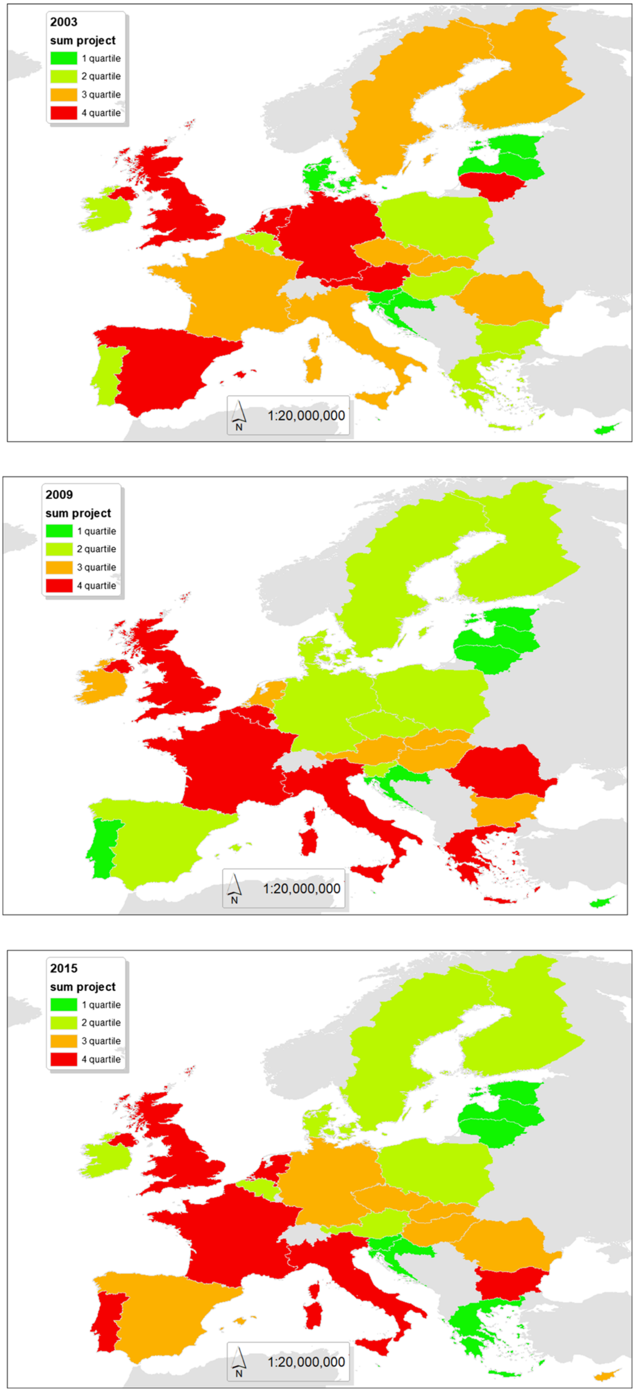
We could say that, in many cases, changes in topological measures anticipate and follow the trends of macroeconomic variables. However, we consider our results exploratory, even though they indicate a clear direction.

5 Conclusions

FDI became a key mode of internationalization that change the geography of production. The mutual economic relationships naturally arising from internationalization strategies create possible paths of economic contagion and constitute a source of intrinsic systemic risks. The latter refers ‘to a situation in which instability in a country leads to instability in another one’ (Recchioni and Tedeschi 2017) through a domino-propagation along the links of the network. We study if and how the topological measurements of the FDI network correlate with macroeconomic variables, with the hypothesis that propagation is strongly affected by the topology itself (i.e., the centrality properties of its nodes). It is in this perspective that our analysis is an assessment of systemic risk transmission.

Instead of the traditional theoretical models of failure propagation or epidemic spreading, we follow an empirical approach with the intention to identify signals of systemic risk based on a double approach: (i) monitoring the evolution of specific topological properties of the network (like centrality measurements), highlighting the

[8] For the sake of brevity, we do not report the results here, but they are available upon request.



2003

2009

2015

Fig. 11 Sum of projects in 2003, 2009, 2015

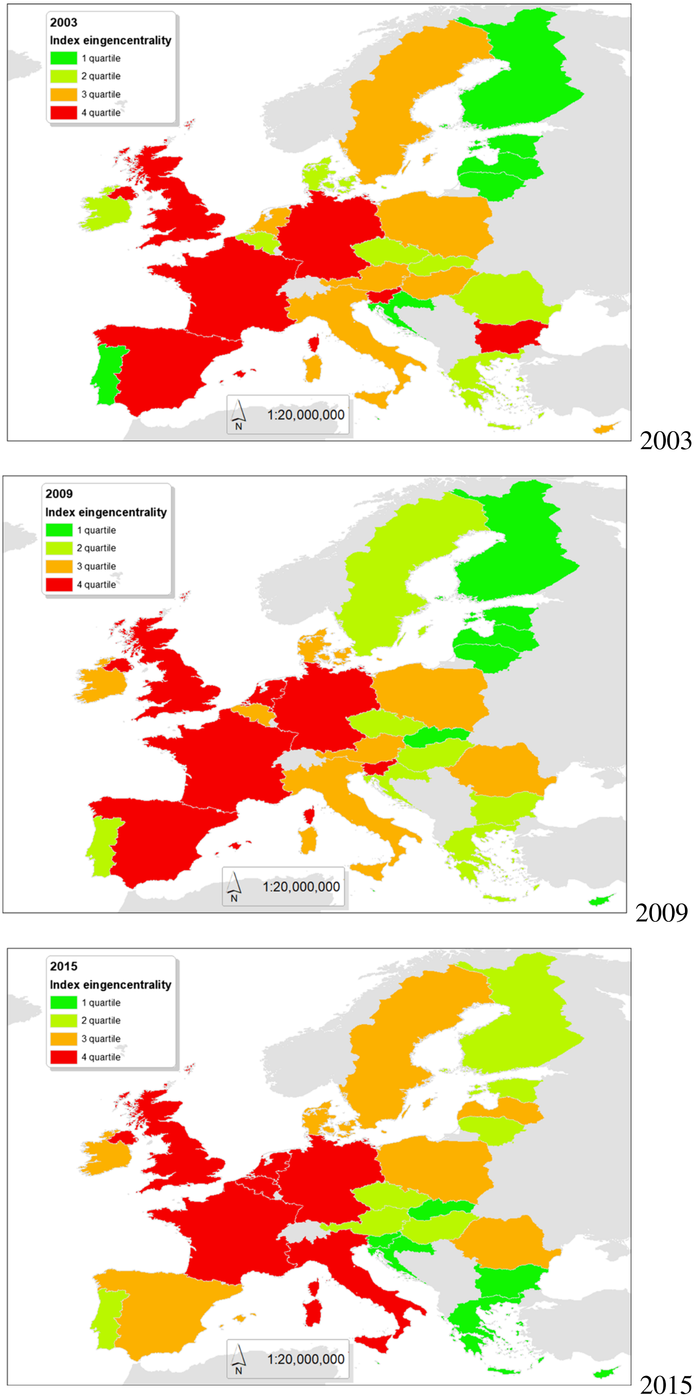


Fig. 12 Maps of eigen-centrality in 2003, 2009, 2015

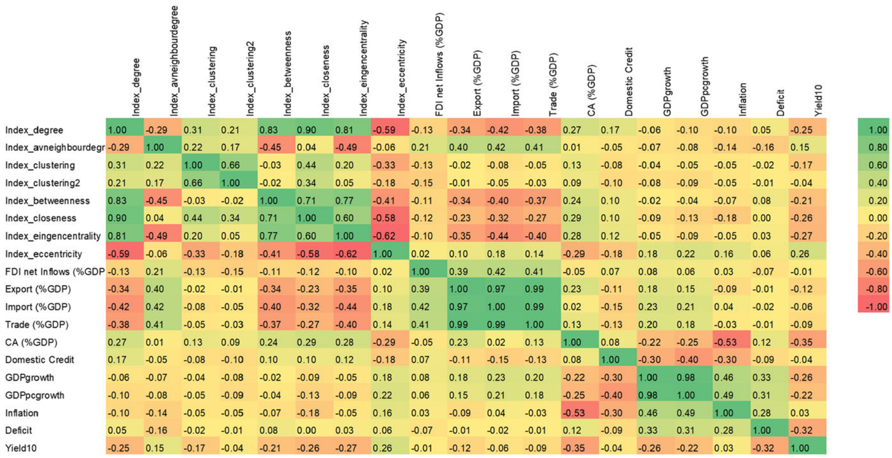


Fig. 13 Actual indexes and actual macro variables

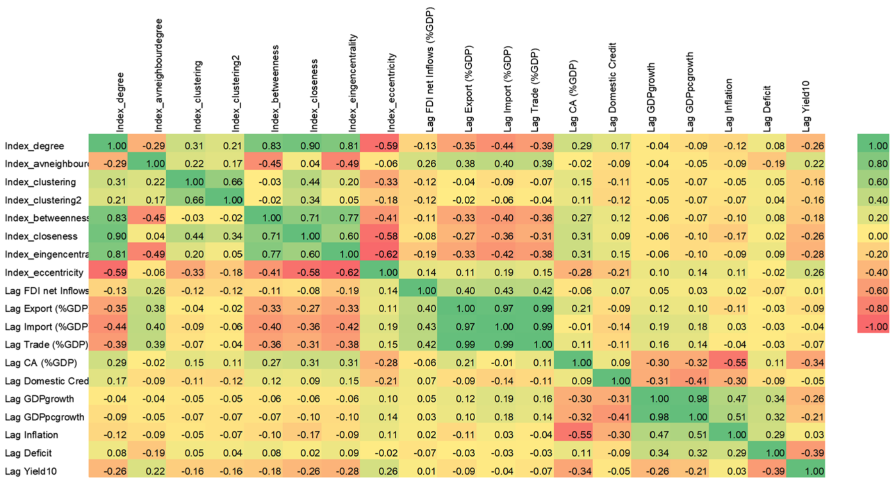


Fig. 14 Actual indexes and lagged macro variables

signs of structural changes during crisis periods and (ii) studying the correlations between macroeconomic variables and early and delayed network indexes.

In particular, a certain cross-correlation between specific lagged centrality measurements and exports, imports, trade and yield emerges, giving us an indication that network topology measures can anticipate changes in these variables. Very significantly, the topological measurements that show the highest correlation with macroeconomic variables are centrality measurements, meaning that the contribution of meso-scale network topology plays a crucial role in systemic risk. Other topological measurements—like degree—that can be reduced to other traditional statistical measurements, do not show the same level of correlation. This is very strong evidence that attention should be paid to network structure in systemic risk assessment.

	Lag Index_degree	Lag Index_avneighbourdegree	Lag Index_clustering	Lag Index_clustering2	Lag Index_betweenness	Lag Index_closeness	Lag Index_eingencentrality	Lag Index_eccentricity	FDI net Inflows (%GDP)	Export (%GDP)	Import (%GDP)	Trade (%GDP)	CA (%GDP)	Domestic Credit	GDPgrowth	GDPpcgrowth	Inflation	Deficit	Yield10
Lag Index_degree	1.00	-0.28	0.32	0.24	0.83	0.91	0.81	-0.59	-0.14	-0.35	-0.44	-0.39	0.28	0.17	-0.12	-0.16	-0.13	-0.02	-0.26
Lag Index_avneighbourc	-0.28	1.00	0.22	0.14	-0.45	0.05	-0.49	-0.06	0.31	0.36	0.37	0.37	0.03	-0.03	-0.17	-0.17	-0.20	-0.20	0.18
Lag Index_clustering	0.32	0.22	1.00	0.63	-0.02	0.45	0.21	-0.33	-0.13	-0.05	-0.10	-0.08	0.10	-0.07	-0.10	-0.12	-0.06	-0.09	-0.10
Lag Index_clustering2	0.24	0.14	0.63	1.00	-0.01	0.34	0.07	-0.16	-0.12	-0.05	-0.09	-0.07	0.08	-0.08	-0.12	-0.13	-0.09	-0.05	-0.08
Lag Index_betweenness	0.83	-0.45	-0.02	-0.01	1.00	0.71	0.77	-0.42	-0.11	-0.34	-0.40	-0.37	0.24	0.10	-0.01	-0.02	-0.06	0.07	-0.23
Lag Index_closeness	0.91	0.05	0.45	0.34	0.71	1.00	0.59	-0.57	-0.05	-0.25	-0.34	-0.30	0.31	0.10	-0.16	-0.20	-0.20	-0.08	-0.25
Lag Index_eingencentra	0.81	-0.49	0.21	0.07	0.77	0.59	1.00	-0.63	-0.19	-0.36	-0.45	-0.40	0.26	0.13	-0.04	-0.07	-0.08	0.03	-0.26
Lag Index_eccentricity	-0.59	-0.06	-0.33	-0.16	-0.42	-0.57	-0.63	1.00	0.03	0.13	0.22	0.17	-0.33	-0.18	0.22	0.24	0.26	0.13	0.20
FDI net Inflows (%GDP	-0.14	0.31	-0.13	-0.12	-0.11	-0.05	-0.19	0.03	1.00	0.39	0.42	0.41	-0.05	0.07	0.08	0.06	0.03	-0.07	-0.01
Export (%GDP)	-0.35	0.36	-0.05	-0.05	-0.34	-0.25	-0.36	0.13	0.39	1.00	0.97	0.99	0.23	-0.11	0.18	0.15	-0.09	-0.01	-0.12
Import (%GDP)	-0.44	0.37	-0.10	-0.09	-0.40	-0.34	-0.45	0.22	0.42	0.97	1.00	0.99	0.02	-0.15	0.23	0.21	0.04	-0.02	-0.06
Trade (%GDP)	-0.39	0.37	-0.08	-0.07	-0.37	-0.30	-0.40	0.17	0.41	0.99	0.99	1.00	0.13	-0.13	0.20	0.18	-0.03	-0.01	-0.09
CA (%GDP)	0.28	0.03	0.10	0.08	0.24	0.31	0.26	-0.33	-0.05	0.23	0.02	0.13	1.00	0.08	-0.22	-0.25	-0.53	0.12	-0.35
Domestic Credit	0.17	-0.03	-0.07	-0.08	0.10	0.10	0.13	-0.18	0.07	-0.11	-0.15	-0.13	0.08	1.00	-0.30	-0.40	-0.30	-0.09	-0.04
GDPgrowth	-0.12	-0.17	-0.10	-0.12	-0.01	-0.16	-0.04	0.22	0.08	0.18	0.23	0.20	-0.22	-0.30	1.00	0.98	0.46	0.33	-0.26
GDPpcgrowth	-0.16	-0.17	-0.12	-0.13	-0.02	-0.20	-0.07	0.24	0.06	0.15	0.21	0.18	-0.25	-0.40	0.98	1.00	0.49	0.31	-0.22
Inflation	-0.13	-0.20	-0.06	-0.09	-0.06	-0.20	-0.08	0.26	0.03	-0.09	0.04	-0.03	-0.53	-0.30	0.46	0.49	1.00	0.28	0.03
Deficit	-0.02	-0.20	-0.09	-0.05	0.07	-0.08	0.03	0.13	-0.07	-0.01	-0.02	-0.01	0.12	-0.09	0.33	0.31	0.28	1.00	-0.32
Yield10	-0.26	0.18	-0.10	-0.08	-0.23	-0.25	-0.26	0.20	-0.01	-0.12	-0.06	-0.09	-0.35	-0.04	-0.26	-0.22	0.03	-0.32	1.00

1.00
0.80
0.60
0.40
0.20
0.00
-0.20
-0.40
-0.60
-0.80
-1.00

Fig. 15 Lagged indexes and actual macro variables

We explain our findings in the following way. At the beginning of the century, the process of globalization and the augmented fragmentation of production prompted firms to invest abroad. At the same time, they tried to diversify by bringing different production tasks to many countries. However, following the emergence of the US crisis, EU firms started to move their investments to groups of countries such as Germany, Great Britain, the Netherlands. As Eastern and Southern Europe markets were considered more risky, they attempted to reduce risk by investing in the main, central EU countries. However, the phenomenon was slightly different according to the sector. In a traditional sector like Industrial Machinery, the above-mentioned trend is very evident, leading to a reduction in the number of investments, while in an emerging sector like Software and IT, after a short-term effect due to the crisis, we observe an increased number of diversified investments.

This could reveal a trade-off between systemic and sharing risk. Moreover, based on our findings, it seems that during a crisis the relationships of mutual dependence between countries become stronger. Secondly, in order to protect traditional markets, policy measures have to be taken.

The EU-FDI network self-organizes itself during crises, in order to reduce the overall systemic risk, by rewiring links towards the safest nodes. Contagion would become more likely if a central country were to face a large idiosyncratic shock, like the structure we observe before 2009. The emergence of a set of key players, with a centrality slightly lower than the initial one, facilitates diversification. From this point of view, even if an increased number of links—in principle—could generate more paths of economic contagion, rewiring connections towards strong economies could make the system safer and less prone to systemic risk.

Acknowledgements We would like to thank Gabriele Tedeschi, who discussed with us the link between topology measures, macroeconomic variables and systemic risks. We also thank Eleni George Papageorgiou, Maria Cristina Recchioni, Thomas Lux and three anonymous referees for their comments and suggestions.

Last but not least, we are grateful to Filippo Santi, our research assistant, and Federico Martellozzo, who created the maps. None of the above are responsible for our errors.

References

Acemoglu D, Ozdaglar A, Tahbaz-Salehi A (2015) Systemic risk and stability in financial networks. Am Econ Rev 105(2):564–608

Alfaro L, Chen M (2014) The global network of multidimensional firms. J Int Econ 94(2):263–276

Arata Y, Chakraborty A, Fujiwara Y, Inoue H, Krichene H, Terai M (2018) Shock propagation through customer-supplier relationships: an application of the stochastic actor-oriented model. In: Cherifi C, Cherifi H, Karsai M, Musolesi M (eds) Complex networks & their applications VI. Complex Networks (2017) Studies in Computational Intelligence, vol 689. Springer, Cham

Asgharian H, Krygier D, Vilhelmsson A (2019) Systemic risk and centrality revisited: the role of interactions. SSRN: https://ssrn.com/abstract=2960629

Battiston S, Puliga M, Kaushik R, Tasca P, Caldarelli G (2012) Debtrank: too central to fail? Financial networks, the fed and systemic risk. Sci Rep 2:541

Berardi S, Tedeschi G (2017) From banks' strategies to financial (in)stability. Int Rev Econ Finance 47(C):255–272

Brandes U (2001) A faster algorithm for betweenness centrality. J Math Sociol 25(2):163–177

Criscuolo C, Timmis J (2017) The changing structure of global value chains: are central hubs key for productivity? OECD working paper

De Benedictis L, Tajoli L (2011) The world trade network. World Econ 34(8):1417–1454

De Masi G (2008) Empirical analysis of the architecture of the interbank and credit market using network theory. In: Networks, topology and dynamics. Springer series lecture notes in economics and mathematical systems, vol 613. Springer Edition

De Masi G, Ricchiuti G (2018) The network of European outward foreign direct investments. In: Smith M, Amighini A, Gorgoni S (eds) Networks of international trade and investment. Vernon Press, Boston

De Masi G, Fujiwara Y, Gallegati M, Greenwald B, Stiglitz JE (2011) Japanese financial credit networks. Evolut Inst Econ Rev 7(2):209–232

De Masi G, Giovannetti G, Ricchiuti G (2013) Network analysis of Italian foreign direct investments. Physica A 392:1202–1214

Fagiolo G, Reyes JA, Schiavo S (2009) The evolution of the world trade web: a weighted-network analysis (2009). J Evolut Econ 20(4):479–514

Freeman LC (1977) A set of measures of centrality based on betweenness. Sociometry 40(35):41

Garas A, Lapatinas A, Poulios K (2016) The relation between migration and FDI in the OECD from a complex network perspective. ACS 19(06–07):1–20

Garlaschelli D, Battiston S, Castri M, Servedio VDP, Caldarelli G (2005) The scale-free topology of market investments. Physica A 350(2–4):491–499

Hautsch N, Schaumburg J, Schienle M (2015) Financial network systemic risk contributions. Rev Finance 19(2):685–738

Iori G, De Masi G, Precup O, Gabbi e G, Caldarelli G (2008) A network analysis of the Italian overnight money market. J Econ Dyn Control 32(1):259–278

Joyez C (2019) Alignment of multinational firms along global value chains: a network-based perspective. GREDEG working papers 2019-05, Groupe de REcherche en Droit, Economie, Gestion (GREDEG CNRS), University of Nice Sophia Antipolis

Joyez C (2017) On the topological structure of multinational network. Physica A 473:578–588

Kamada T, Kawai S (1989) An algorithm for drawing general undirected graphs. Inf Process Lett 31(1):7–15

Krackhardt D (1990) Assessing the political landscape: structure, cognition, and power in organizations. Adm Sci Q 35(2):342–369

Kuzubas TU, Ömercikoglu I, Saltoglu B (2014) Network centrality measures and systemic risk: an application to the Turkish financial crisis. Physica A 405:203–215

Lenzu S, Tedeschi G (2012) Systemic risk on different interbank network topologies. Phys A Stat Mech Appl 391(18):4331–4341

Metulini R, Riccaboni M, Sgrignoli P, Zhu Z (2017) The indirect effects of foreign direct investment on trade: a network perspective. World Econ 40(10):2193–2225

Newman MEJ (2010) Mathematics of networks: an introduction to the mathematical tools used in the study of networks, tools that will be important to many subsequent developments. In: Newman M (ed) Networks: an introduction. Oxford University Press, Oxford

Pajek, Program for large network analysis, Vers.5.03. http://vlado.fmf.uni-lj.si/pub/networks/pajek/

Pastor-Satorras R, Vespignani A (2001) Epidemic spreading in scale-free networks. Phys Rev Lett 86(14):3200–3

Recchioni MC, Tedeschi G (2017) From bond yield to macroeconomic instability: a parsimonious affine model. Eur J Oper Res 262(3):1116–1135

Rungi A, Morrison G, Pammolli F (2017) Global ownership and corporate control networks. Working papers 07/2017, IMT Institute for Advanced Studies Lucca, revised Sep 2017

Sabidussi G (1966) The centrality index of a graph. Psychometrika 31:581–603

Schwarcz SL (2008) Systemic risk. Georget Law J 97:193

Wall RS, van der Knapp GA (2011) Sectoral differentiation and network structure within contemporary worldwide corporate networks. Econ Geogr 87(3):267–308

Zhao L, Park K, Lai YC (2004) Attack vulnerability of scalefree networks due to cascading breakdown. Phys Rev E 70:035101